

Blur Parameter Identification using Support Vector Machine

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Abstract—This paper presents a scheme to identify the blur parameters using support vector machine (SVM) Multiclass approach has been used to classify the length of motion blur and sigma parameter of atmospheric blur. Different models of SVM have been constructed to classify the parameters. Experimental results show the robustness of the proposed approach to classify blur parameters.

Index Terms—Classification, support vector machine (SVM), motion blur, point spread function(PSF)

I. INTRODUCTION

The goal of image restoration is to obtain visual information from a degraded observation. Image restoration finds application in many areas like photographic blur, astronomical imaging, remote sensing, medical imaging etc. Images may be blurred by the imaging device, or the medium through which the light propagates. The relative motion between the imaging device and the object also leads to image blurring. In most of the applications, the blurring process is assumed to be linear and it is mathematically represented as 2D convolution between the original image $f(x, y)$ and the degradation function $h(x, y)$ also known as point spread function (PSF). Thus $g(x, y)$ can be written as

$$g(x, y) = f(x, y) * h(x, y) \\ = \sum_{p, q} f(p, q)h(x - p, y - q) \quad x, y, p, q \in Z \quad (1)$$

Where $*$ denotes the linear convolution operator and Z is the set of integers. Image restoration techniques are oriented towards approximating the true image from the degraded observation. In classical restoration, it is assumed that the PSF is known apriori and the task is just to invert the degradation process. However, in many practical situations, the point spread function [1] is not available and it is difficult to obtain the sense of the original image. This situation arises because of some practical constraints like characterizing the degradation function in astronomical imaging and may be due to hazard of using stronger beam for a good image resolution in medical imaging. In such situations blind image deconvolution is inevitable for image restoration. There exists a variety of blind image restoration schemes proposed in the literature [8, 9, 10]. Blind image deconvolution problem has been classified into two categories. In the first category, blur and its parameters are identified and the PSF is constructed.

Then image is restored using any of the classical restoration methods. In the second category PSF estimation and image restoration are achieved simultaneously. Our work falls in the first category where PSF parameters are identified before image restoration. In this paper, we have identified the length of motion blur and sigma parameter of atmospheric turbulence blur which decides the severity of blur. Motion blur parameter identification have been proposed in many literature [2, 3, 4, 5, 7]. Hough transform has been used to estimate blur length by detecting the lines in the spectrum of the degraded image [5]. Authors in [6] have proposed an adaptive adaline network to estimate motion length of a degraded image. Igor Aizenberg and his team [4] developed a method to restore horizontal motion blurred image. Their work needs a rough estimation of motion length which is achieved using power spectrum. Similarly in [9] a method has been proposed to restore images degraded with atmospheric blur. Principal component analysis (PCA) has been used in [8] to deal with the turbulence blur. The present work attempts to estimate length parameter of motion blurred image and sigma parameter of turbulence blurred image. We utilize the blur parameter subsequently to construct the PSF for restoration. Though there are large volume of work reported, researchers are still active in this direction in order to improve the image quality and peak signal to noise ratio (PSNR). In this paper we have utilized the support vector machine as a classifier to classify the blur parameter.

The rest of the paper is organized as follows. Different blur models are described in section II. Support vector machine and multiclass approach has been provided in section III. Experimental results for the proposed approach have been provided in section IV. Finally section V gives the concluding remarks.

II. BLUR MODELS

A. MOTION BLUR MODEL

The point spread function for motion blur can be described by the following equation.

$$h(x, y) = \begin{cases} \frac{1}{L} & \text{if } |x| \leq \frac{L}{2} \cos \phi \quad y = x \tan \phi \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

where L is the length of motion blur and ϕ is the angle of motion blur.

B. ATMOSPHERIC TURBULENCE MODEL

The point spread function for atmospheric blur is described as

$$h(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (3)$$

where σ controls the severity of degradation.

III. SVM BASED BLUR IDENTIFICATION

A support vector machine classifies data into two classes by separating them into two categories. SVM is also used to perform multi class classification [11, 15]. It distinguishes one class from others by constructing a hyper plane with maximum margin. An optimal hyper plane is constructed by solving a quadratic optimization problem. SVM models are equivalent to the classical multi layer perceptron(MLP) neural network where weights are optimized in order to classify the test data accurately. Traditional neural networks solve a non convex unconstrained minimization problem. SVM models also use a training data set (X_i, Y_i) like MLP and update the weights. However, SVM uses a kernel function and weights of the networks are found by solving a quadratic programming problem with linear constraints. SVM solves the following optimization problem

$$\begin{aligned} \min_{W, b, \xi, \xi^*} & \frac{1}{2} W^T W + C \sum_{i=1}^n (\xi_i + \xi_i^*) \\ \text{subject to } & y_i - (W^T \phi(x_i) + b) \leq \varepsilon + \xi_i \\ & (W^T \phi(x_i) + b) - y_i \leq \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geq 0; i = 1, 2, \dots, n \end{aligned} \quad (4)$$

Where ξ_i is the upper training error and ξ_i^* is the lower training error subject to $|y_i - (W^T \phi(x_i) + b)| \leq \varepsilon$ and ε is a threshold. C is the penalty parameter.

A. FEATURE SELECTION

The variance parameter decreases with the blurring strength in a blurred image Change of variance with blur length for different images are shown in Figure.1 We have used variance as one of the criteria to select the samples from the blurred image. It is also well known that edges in an image play a major role for image analysis. The high frequency regions in a cameraman image for different motion blur length are shown in Figure.2. It is evident from Figure 2 as the blur length increases, edges becomes smoother. The smoothness in the blurred image can be measured using variance. We construct the training set by taking the regions in the blurred image having higher variance. Such regions are searched by taking a 7x7 window and sliding this from top to bottom. If g represents the blurred image with blur length L , then we select the gray values of the window g_w whose variance is larger. The feature vector is constructed as $[g_w(:); L]^T$ where $g_w(:)$ represents lexicographic ordering of the gray values of the window having larger variance and L is the corresponding blur length.

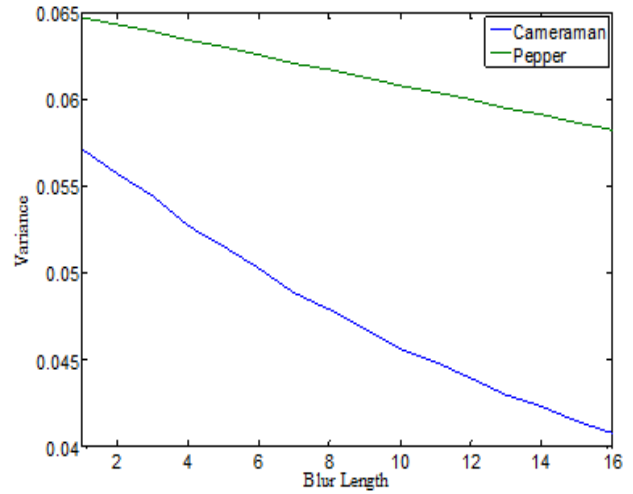


Figure1. Variance curve for different blurred images with blur length

B. BLUR PARAMETER CLASSIFICATION

The multi class SVM has been used to classify the blur parameter. Several approaches to multiclass SVM have been proposed in the literature [12, 13, 14]. These methods decompose the multiclass problem into number of two class problems. They use different decomposition methods like one versus rest, one versus one etc. Using the SVM for blur parameter classification is straightforward.

First we construct a training set using the feature vectors as described above and train the feature samples with a multiclass SVM. In the testing phase, features of the blurred image with different blur length are collected and fed to the trained SVM model. The output of the SVM is the identified blur length. The sigma parameter of the atmospheric turbulence blur has been identified in the same way by constructing another multi class SVM model. Details of the experiments conducted are described in the simulation section.

III. SIMULATION RESULTS AND DISCUSSION

Experiments have been conducted in the MATLAB environment to show that the trained SVM model can be used to identify the blur parameter in new images. Standard images like Cameraman, Lena and Pepper are used for both training and testing. All the images used for training and testing are scaled in the range [0, 1] in the spatial domain. We have used a window size of 7x7. So the size of one sample vector used in the SVM is [49x1]. The SVM model trained with *Cameraman* image is tested with a different image.

A. Experiment 1: Cameraman SVM model for motion blurred image

The *Cameraman* image is horizontally motion blurred with $L = 2$ to 30 with a gap of 2. The 1844 samples from the blurred image have been taken by considering the window whose variance is larger than 0.02. The SVM is trained with the collected samples of blurred cameraman image and a SVM model is created.

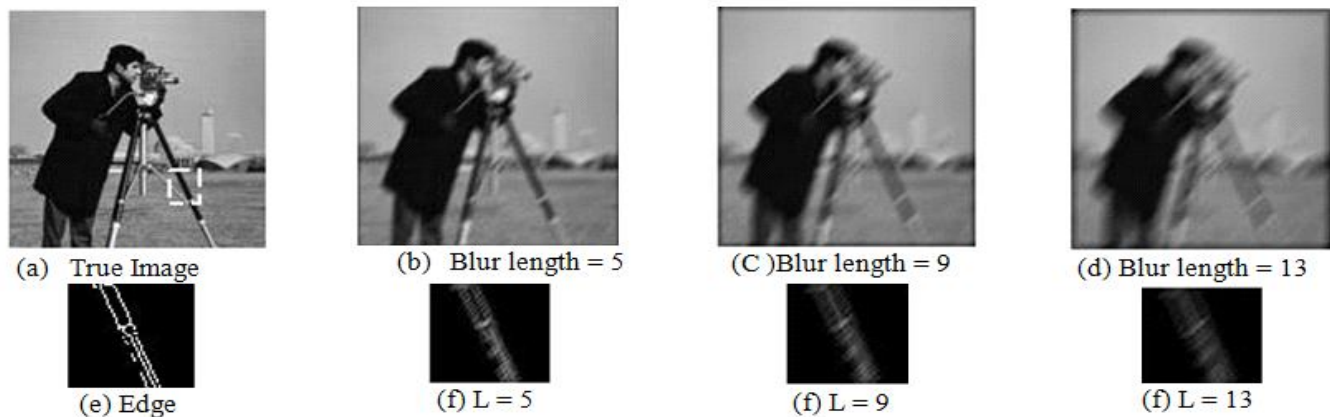


Figure 2 Behavior of an edge under motion blur of various Blur length with 45° angle

The SVM model is validated by testing the samples of cameraman image as well as *Lena* image. The vote count for each of the estimated class is for cameraman image and *Lena* image are noted and has been shown in TABLE I & II respectively. Values in each column show the number of votes won by different blur lengths. The maximum vote obtained by any row in a particular column is the estimated class which is equal to the blur length. We should note that the samples from *Lena* image are different from the sample used in the training. It is clear from the Table 1 that the proposed multiclass SVM identifies the blur length accurately for the same image as well as different image. To create the SVM model LIBSVM package [16] is used with the default radial basis function. The value of C is chosen on a trial and error basis and for the *cameraman* image SVM model it is taken as 1. Error tolerance and Gamma value are chosen to be 0.0001 and 5 respectively.

TABLE I. BLUR IDENTIFICATION PERFORMANCE OF MULTICLASS SVM FOR CAMERAMAN IMAGE

Estimated Blur Length	Actual Blur Length			
	5	9	13	17
5	861	128	29	16
9	44	321	64	28
13	3	22	154	41
17	5	9	30	88

TABLE II. BLUR IDENTIFICATION PERFORMANCE OF MULTICLASS SVM FOR LENA IMAGE

Estimated Blur Length	Actual Blur Length			
	5	9	13	17
5	689	156	51	19
9	53	331	72	35
13	6	16	168	39
17	8	12	35	97

These parameters can also be optimized for different images and different degradation. After the blur parameter is identified PSF is constructed and the degraded images are restored. The restoration result for the *cameraman* image is shown in Figure 3.

B. EXPERIMENT 2 PEPPER SVM MODEL FOR ATMOSPHERIC BLURRED IMAGE

The Pepper image is degraded with atmospheric turbulence with different sigma (σ) values in the range [0.5 -5] using the inbuilt function available in MATLAB. The training samples of the blurred Pepper image are accumulated using the same procedure as explained in Experiment 1. Total 1392 samples; have been used for training the SVM. To validate the effectiveness of the proposed scheme, testing samples from cameraman image also have been used. The performance of the multi class SVM for different images has been shown in TABLE III and IV respectively. The results in the TABLE's show that the proposed multiclass SVM also works well for images degraded with atmospheric turbulence blur and it achieves generalization in terms of different images. Same voting strategy has been followed in this experiment to identify the actual sigma value. The value of C has been kept 1 and RBF kernel has been used in the LIBSVM package. Gamma value and error tolerance are chosen to be 4 and 0.0001 respectively. The restored image is obtained after constructing the PSF from the identified sigma parameter. The restoration results for Pepper image is shown in Figure 4.

TABLE III. BLUR IDENTIFICATION PERFORMANCE OF MULTICLASS SVM FOR PEPPER IMAGE

Estimated Sigma	Actual Sigma				
	0.5	1	2	3	4
0.5	444	6	0	0	1
1	3	222	1	0	0
2	1	11	128	48	14
3	0	14	52	103	97
4	1	2	43	83	129

TABLE IV. BLUR IDENTIFICATION PERFORMANCE OF MULTICLASS SVM FOR CAMERAMAN IMAGE

Estimated Sigma	Actual Sigma				
	0.5	1	2	3	4
0.5	312	6	0	0	0
1	23	252	1	0	2
2	12	51	138	38	24
3	0	14	46	93	67
4	1	2	23	34	85

CONCLUSIONS

A novel method has been proposed to identify the blur parameter from the blurred images. The blur identification problem is modeled as a multiclass classification problem and has been solved using support vector machine. The suggested scheme achieves generalization in terms of different images and estimates the blur parameters accurately. The proposed scheme is applicable to images degraded with horizontal motion blur and images degraded with atmospheric turbulence blur. However, the proposed method can also be applied to estimate angle of motion blur by constructing another SVM model.

REFERENCES

- [1] R.C.Gonzalez, R.E.Woods "Digital Image Processing", Addition Wesley, 2nd edition
- [2] Y.Zhang, C.Wen, "Estimation of motion parameters from blurred images" *Pattern Recognition Letters*, pp 425–433.. 2000
- [3] M. Chang, A. Tekalp, A. Erdem, "Blur identification using the bispectrum," in, *IEEE Transactions on Signal Processing* vol. 39, pp. 2323–2325. 1991
- [4] I. Aizenberg, D. V. Paliy, J. M. Zurada, J. T. Astola, "Blur identification by multilayer neural network based on multivalued neurons", *IEEE Transaction on Neural Networks*. vol ,pp 883-898, 2008
- [5] R. Lokhande, K. V. Arya, P. Gupta, "Identification of parameters and restoration of motion blurred images", in: *Proceedings of the ACM Symposium on Applied Computing* vol 9,pp 301-305, 2006.
- [6] W.-G. He, S.-F. Li, G.-W. Hu, "Blur identification using adaptive adaline network," *IEEE International Conference on Machine Learning and Cybernetics, Guangzhou, China*, pp. 5314-5317, 2005
- [7] M.E.Moghaddam, M.Zamzad, "Robust estimation of motion blur parameters" *5th International Conference on Advanced Pattern Recognition (ICAPR)*. 2003
- [8] Dalong Li, Russell M. Mersereau, and Steven Simske, "Atmospheric Turbulence-Degraded Image Restoration Using Principal Components Analysis", *IEEE Geoscience and Remote Sensing Letter*, vol 4, pp 340-344, July 2007
- [9] Omri Shacham, Oren Haik, and Yitzhak Yitzhaky, "Blind restoration of atmospherically degraded images by automatic best step-edge detection", *Pattern Recognition Letters*, vol 28,pp 2094-2103, November 2007
- [10] Dalong Li, Russell M. Mersereau, and Steven Simske., "Blind Image Deconvolution Through Support Vector Regression", *IEEE Transactions on Neural Networks*, vol 18, pp 931-935, may 2007
- [11] Vladimir N. Vapnik., "The Nature of Statistical Learning Theory", *Springer Verlag*, Newyork 1995
- [12] A. Bordes, L. Bottou, P. Gallinari, and J. Weston," Solving Multiclass Support Vector Machines with LaRank", *In 24th International Conference on Machine Learning, Corvallis, USA*, June 2007
- [13] Chih-Wei Hsu and Chih-Jen Lin., "A Comparison of Methods for Multiclass Support Vector Machines", *IEEE Transactions on Neural Networks*, vol 13 pp 415-425, March 2002
- [14] Ben Fei and Jinbai Liu., "Binary Tree of SVM: A New Fast Multiclass Training and Classification Algorithm", *IEEE Transactions on Neural Networks*, vol 17, pp 694-704 May 2006
- [15] Kai-Bo Duan and S. S. Keerthi, "Multiple Classifier Systems, chapter Which Is the Best Multiclass SVM Method? An Empirical Study", *Lecture Notes in Computer Science. Springer Berlin* 2005
- [16] C. C. Chang and C. J. Lin, "LIBSVM: A library for support vector machines", [Online]. Available: <http://www.csie.ntu.edu.tw/~verb-cjlin/libsvm> 2001

